The Impact of Education on Poverty

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Abstract: The effects of education on poverty has often been discussed and analyzed by economic researchers. This paper aims to do the same, researching the education-poverty relationship. In this paper, we create a regression model with education level as our independent variable and its causality upon the income to poverty ratio. Using data compiled from the US Census Bureau, we created a single variable regression model estimating the ceteris paribus effect of education on income to poverty. We followed this regression model with several others, separating our data into different population groups, to compare the effect of education within these groups. The results of our regression model indicate a positive correlation between education and the income to poverty ratio with a coefficient of 15.5 indicating that each additional threshold of education achievement results in a 15.5% increase in the income to poverty ratio. When contrasting this coefficient with different population groups, such as minorities and those within poverty, we can see that the education coefficient varies, many times drastically. We also see, through multiple variable regression models, the effects other independent variables have on poverty.

Keywords: Regression model, education, poverty, income

Introduction

A good education is often thought of as almost a guarantee of future success and increased future earnings. In the United States enrollment in colleges and universities continues to rise, as well as enrollment in other post-secondary institutions, yet income inequality and poverty continue to be a problem. Is it possible that as more people become educated, the education becomes less valuable on the job market? With so many people earning college degrees, the competitiveness for jobs that require such education increases, providing the employers with more options, and less incentive to provide a high wage to attract talented individuals. Increased competitiveness on the job market has led to many people being underemployed, but are these individuals below the poverty line? Poverty has long been associated with underprivileged and undereducated people, but this project's aim is to determine the how education affects poverty. Our hypothesis is that education attainment has a positive effect on the income to poverty ratio.

Other factors that we have included in our sample data that could impact poverty include the number of hours worked per week by an individual, household income, and whether or not the individual receives food stamps. Additionally, our data includes children under 16 years of age, allowing us to examine their poverty level with respect to each of the parents' employment status. Our expectations are that income and poverty level are both still negatively correlated with education level, both in the direct sense by improving an individual's employability prospects and through externalities benefiting the poor that arise from an increased level of education, such as better healthcare. A significant jump in income and drop in poverty levels for anyone with a Bachelor's degree or higher is still very likely, even with the increase in graduates and recent recession. We feel that our analysis will confirm the belief that the best possible way to increase expected earnings and decrease the likelihood of an individual being below the poverty line is to pursue a college degree.

Literature Review

The link between education and poverty has been studied extensively, and proven to be statistically significant in many instances using different metrics for education and poverty. The following papers were reviewed because we found them to be relevant to our project while each having a unique aspect. Similarly, we wanted to not only research the relationship of education on poverty, but the relationship of education on poverty within different population groups. With several regression models, our unique aspect is a comparison between these population groups.

Dhongde and Haveman (2015) estimate a multi-dimensional poverty index for the United States. The goal of creating this new index is to provide a more specific and complete view of the impoverished, looking not only at low income, but also economic and individual well-being. The dimensions of deprivation that this research team (2015) use are four: health, education, standard of living, and housing. Each dimension has different indicators including health insurance coverage, completion of school, ability to speak English, income to poverty ratio, employment, occupants per housing unit, and others. Dhongde and Haveman (2015) estimate that 20 percent of the total population exhibited some form of multidimensional poorness. Of those 20 percent, they found that 40 percent had not completed high school and 16 percent lived in a crowded house / had no household members fluent in English. This data is also decomposed in population subgroups to analyze the difference in poverty among different factors, such as age, gender, race, and region. Findings included Asian subgroups with higher than average deprivation in two indicators: crowded houses and lack of English fluency, yet with lower deprivation when analyzing income identifiers. The Northeast and Midwest regions had a less than average proportion of multidimensionally poor while the South and West had a greater than average proportion. Dhongde and Haveman (2015) concludes with saying that a large proportion of the overall U.S. population, 42 percent, is deprived in at least one of the indicators of well-being not necessarily income.

De Silva and Sumarto (2015) analyze the effect of health and education capital on economic growth and poverty within Indonesia. Because both educational access and health quality is quite different around the country, the researchers looked within the district level to analyze economic growth. They discusses the neoclassical model in which both health capital and education capital provide a cross-district increase in economic growth and decrease in poverty. The hypothesis based around the neoclassical model directly relates the growth of human capital with higher income, stating that education capital differences account for a significant part of the variation observed in regional income distribution. De Silva and Sumarto (2015), however, note that other researchers have argued that schooling has a limited impact on economic growth for developing countries. Contrary to the previous researchers, De Silva and Sumarto (2015) did find that increased education capital to be associated with a lower level of poverty within districts. Also noteworthy is the positive correlation found between the prevalence of poor immunization coverage and water-borne diseases and the poverty rate. De Silva and Sumarto (2015) attribute poorer districts with both lower education and higher disease. They conclude that this research suggests that the neoclassical model is accurate and that economic growth is crucial to poverty reduction.

Blank (2008) states that current poverty measurement methods in the US are highly flawed and how the US could follow examples set by other developed countries. The current standard, measuring people who have fallen below a level has issues because it fails to measure the depth of economic need; there is no measure or mention of those who become poorer from having already been poor. In 1995, an NAS report suggested basing the threshold on expenditures on necessities such as food, housing and clothing, and then taking into account medical expenses and costs arising from work, such as travel and child-care expenses, and continually adjusting this to reflect changing economic climates. Blank (2008) conclusively suggests installing a committee to continually update the threshold and to take power away from the president, to allow public programs to choose their own eligibility cutoffs based on several poverty guidelines, and to commission work to develop a list of key measures of economic deprivation beyond income poverty in order to further understand the severity of poverty for those under the poverty threshold.

In their paper, Janjua and Kamal (2011) seek to expose the reasoning behind why people are poor across the world, focusing on the effects of education on poverty in not only the direct sense, but also in a more circuitous manner. They cite examples from studies such as better education leading to better farming methods, which lead to higher crop yields and a greater income, reducing the probability that a farmer is under the poverty line. They quote Berg (2008) in saying that the three mechanisms in which education affects poverty are:

1. Higher levels of education lead to higher earnings
2. Higher (and better quality) levels of education lead to more economic growth which increases economic opportunities
3. Higher levels of education lead to higher social benefits and helping the poor, improving healthcare.

From their studies, they find that a high level of income per capita growth is a moderate factor in alleviating poverty, that a decrease in income inequality played a stronger role only in countries with higher per capita incomes, and finally and most importantly, that secondary education played the greatest role in poverty alleviation.

Data

The data for this paper was collected by the United States Census Bureau, more specifically in the American Community Survey(ACS). We accessed the Public Use Microdata Sample(PUMS) through the tool called DataFerrett, which allowed us to specifically select certain variables that were collected from the ACS. Our dataset contains 16 variables and 3,132,795 observations; however, a significant number of these observations are of children. We are only interested in the effect of education on poverty levels in adults, as most children are still in the process of completing their primary education. To address this, we will use the Age variable to drop all observations under 18 years of age. This reduces our number of observations to 2,469,680.

The dependent variable is the poverty to income ratio provided in the ACS. The variable represents percentages ranging from 0-501. Any value of 501% represents values of 501% and higher, estimated to 501% to reduce the effect of outliers. From this poverty to income ratio, we created another variable to represent those individuals that are technically living in poverty which we have named poverty; this includes all individuals in the survey with a poverty to income ratio of less than or equal to 100%. We will use this variable to for a secondary analysis of the effect of education on those within poverty, in addition to our analysis of the entire sample.

Income-to-poverty ratio recode

	Percentiles	Smallest		
1%	0	0		
5%	45	0		
10%	84	0	Obs	2356398
25%	173	0	Sum of Wgt.	2356398
50%	328		Mean	317.0337
		Largest	Std. Dev.	164.0745
75%	501	501		
90%	501	501	Variance	26920.45
95%	501	501	Skewness	-.2885139
99%	501	501	Kurtosis	1.696184

The table above provides some basic information on the income to poverty ratio variable. The mean ratio is 317, meaning the average person in the survey has an income that is 317% of their respective poverty threshold. The poverty threshold changes depending on the dynamics of each person's family and living situation. The standard deviation is 164%, while the minimum is 0 and maximum is 501, due to the ranges provided by the ACS. Using the "count if" command in Stata, we can see that 435,508 individuals are living in poverty, or 14.5% of our sample.

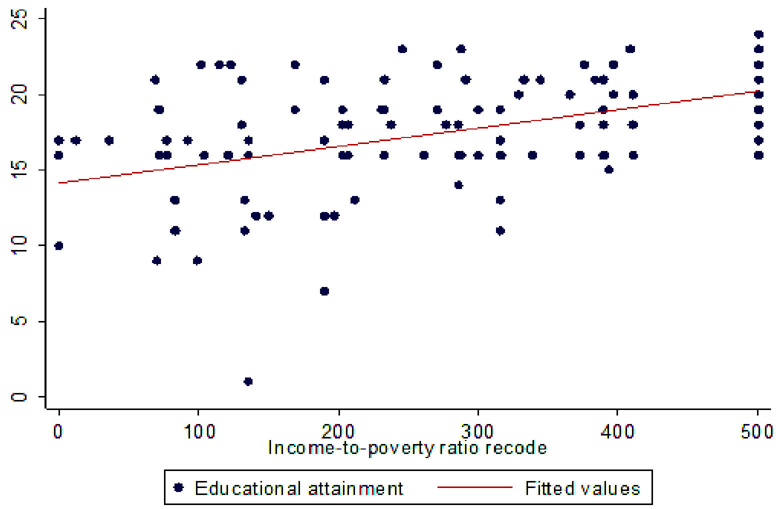
```
. count if POVPIP <=100
435508
```

The primary independent variable is education. The ACS asks respondents what the highest level of education he or she has completed, and codes this using numbers 0 through 24. The numbers represent primary grade levels and post-secondary attainment, including Associate's degree through a PHD or other professional degree.

Educational attainment

	Percentiles	Smallest		
1%	1	1		
5%	12	1		
10%	14	1	Obs	2469680
25%	16	1	Sum of Wgt.	2469680
50%	19		Mean	17.90016
		Largest	Std. Dev.	3.703283
75%	21	24		
90%	22	24	Variance	13.71431
95%	22	24	Skewness	-1.743976
99%	24	24	Kurtosis	8.317228

The average level of education is 17.9, which corresponds to completion of the 12th grade, with some college attended, but less than 1 year. The median is 19, which is 1 or more years of college completed without a degree, meaning 50% of the sample has an education level of a high school diploma, with some college credit. There is a positive correlation between educational attainment and the income to poverty ratio, as shown in the scatter plot below. We will be able to further analyze this relationship when we perform a regression analysis on these variables.



We will employ many other independent variables in addition to educational attainment. In our first multiple variable model we will include number of hours worked per week, number of people in a family, and the number of workers in a family. Another one of our models will include the ability to speak English, the cost of monthly housing rent as a percentage of gross income, and whether or not a respondent has health insurance coverage. All of these variables should help to explain poverty levels, but there are potentially far more factors that we will not be able to include. However, we are going to further separate the data to determine how poverty levels change with respect age, sex, and race.

We have affirmed that our data fits within the Gauss Markov Assumptions. We model our variables in a linear population model. We have a random sample of many observations that follow our model. We have made sure that there is no exact linear relationships among our independent variables. Our expected error is zero given the values of our independent variables and the error has the same variance given the values of our variables showing homoskedasticity. This shows that our regression model falls within the Gauss Markov Assumptions.

Simple Regression Models

The first simple linear regression model will include the income to poverty ratio as the dependent variable, with educational attainment as the independent variable. The model and results are below:

$$POVPIP = \beta_0 + \beta_1(SCHL) + u$$

Source	SS	df	MS
Model	7.8357e+09	1	7.8357e+09
Residual	5.5600e+10	2356396	23595.1644
Total	6.3435e+10	2356397	26920.4547

Number of obs	= 2356398
F(1,2356396)	= .
Prob > F	= 0.0000
R-squared	= 0.1235
Adj R-squared	= 0.1235
Root MSE	= 153.61

POVPIP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SCHL	15.5065	.0269083	576.27	0.000	15.45376	15.55924
_cons	38.59214	.4934296	78.21	0.000	37.62503	39.55924

This simple regression returns a coefficient on the SCHL variable of 15.5, with a standard error of 0.027, t-statistic of 576.3 and p-value of 0.000. The R-squared is 0.1235, meaning that educational attainment explains 12.35% of the variability in the income to poverty ratio around its mean. Combining the R-squared with our very high t-statistic and very small p-value, we can confidently say that educational attainment is a statistically significant variable at all confidence levels. This verifies our hypothesis that educational attainment is positively correlated with the income to poverty ratio.

Now we want to look at only individuals that are in poverty, and the effect that education has on these individuals. The model and results are below:

$$InPOV = \beta_0 + \beta_1(SCHL) + u$$

Source	SS	df	MS
Model	1967477.47	1	1967477.47
Residual	332004846	297502	1115.97517
Total	333972323	297503	1122.58472

Number of obs	= 297504
F(1,297502)	= 1763.01
Prob > F	= 0.0000
R-squared	= 0.0059
Adj R-squared	= 0.0059
Root MSE	= 33.406

In_POV	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
In_POV_SCHL	-.5913308	.0140832	-41.99	0.000	-.6189335	-.563728
_cons	61.00472	.235047	259.54	0.000	60.54404	61.46541

This model results in a statistically significant value for education of people in poverty, but it is a negative relationship. The R-squared is very small at 0.0059, but nevertheless the negative relationship is unexpected. In order to figure out why the relationship is negative we limited some variables. First, we looked at only individuals with a high school diploma or less. This regression still returned a statistically significant value of -0.439, but with a smaller R-squared. The results remain in conflict with the widespread notion that more education will lead to higher wages, and as a result, a higher income to poverty ratio. Next, we decided to look at individuals with at least an Associate's degree.

Source	SS	df	MS
Model	267085.193	1	267085.193
Residual	59932776.7	50953	1176.23647
Total	60199861.9	50954	1181.45508

Number of obs	=	50955
F(1, 50953)	=	227.07
Prob > F	=	0.0000
R-squared	=	0.0044
Adj R-squared	=	0.0044
Root MSE	=	34.296

In_POV	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
In_POV_SCHL_CD	-2.608972	.1731378	-15.07	0.000	-2.948324	-2.26962
_cons	103.0366	3.629086	28.39	0.000	95.92354	110.1496

The results of this regression were even more surprising, with a -2.6 coefficient on our educational attainment variable, which only includes individuals with some sort of secondary degree. This value is statistically significant, but the R-squared is still very low, at 0.0044. Our next thought was to control for age, as maybe too many young people with large amounts of student loans, and entry-level jobs were impacting the results. We decided to look at only people in poverty, with at least an Associate's degree, and 35 years of age or older. All of these restraints resulted in increasing our negative coefficient from -2.6 to -2.09. This value is statistically significant, while the R-squared remained small, at 0.0032. All of the models we have used so far for individuals in poverty have resulted in statistics that run contrary to conventional wisdom; however, we will revisit this inconsistency in the next section, which looks at multiple variable regressions.

Multiple Variable Regression Models

Continuing with our analysis of our in poverty sample, we are going to add more explanatory variables to the model. The best model we were able to achieve contained the following variables: educational attainment, number of hours worked per week, number of people in a family, number of workers in a family, ability to speak English, and cost of housing rent as a percentage of income. The model and results are below:

$$InPOV = \beta_0 + \beta_1(SCHL) + \beta_2(WKHP) + \beta_3(NPF) + \beta_4(WIF) + \beta_5(ENG) + \beta_6(GRPIP) + u$$

Source	SS	df	MS
Model	9858922.7	6	1643153.78
Residual	62842110.3	82938	757.699852
Total	72701033	82944	876.507439

Number of obs	= 82945
F(6, 82938)	= 2168.61
Prob > F	= 0.0000
R-squared	= 0.1356
Adj R-squared	= 0.1355
Root MSE	= 27.526

In_POV	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SCHL	.0904899	.0244253	3.70	0.000	.0426164	.1383633
WKHP	.2831967	.0057628	49.14	0.000	.2719016	.2944918
NPF	-.2330499	.0607425	-3.84	0.000	-.3521048	-.113995
WIF	2.796667	.1460257	19.15	0.000	2.510458	3.082876
ENG	1.375694	.0827904	16.62	0.000	1.213426	1.537963
GRPIP	-.2713436	.0033234	-81.65	0.000	-.2778575	-.2648298
_cons	64.51716	.5263454	122.58	0.000	63.48552	65.54879

This model explains more of the variability in the income to poverty ratio of individuals in poverty, with an R-squared of 0.1356. The coefficients on all of the variables are statistically significant at all levels, with p-values of 0.000 across the board. The coefficient on educational attainment increases from various negative values in the previous models, to a positive 0.0905, with a standard error of 0.0244, and t-statistic of 3.7. The coefficient changing from negative in our simple regression models, to positive in our multiple regression model, could signal a problem with multicollinearity; however, our sample size is so large at 82,945 individuals, we should not worry too much about multicollinearity. There are two negative coefficient values in this model, for number of people in a family at -0.233, and for cost of rent as a percentage of income at -0.271. Both of these values are sensible though, as an increase in family size is expected to result with a decrease in the income to poverty level, as the poverty level for a larger family increases. The same can be said for the cost of rent, as an increase in rent is expected to decrease the income to poverty level, as more money is now spent on rent than on other necessities. Now, we will return to analyzing our full sample, including both individuals in poverty, and individuals not in poverty.

Our next model is going to look at the poverty to income ratio for all individuals as the dependent variable, with educational attainment as the primary independent variable, as well the number of hours worked per week, the number of people in a family, and the number of workers in a family. The additional explanatory variables are all related to family dynamics and labor, which is why we chose to group them together in this model. The model and regression results are below:

$$POVPIP = \beta_0 + \beta_1(SCHL) + \beta_2(WKHP) + \beta_3(NPF) + \beta_4(WIF) + u$$

Source	SS	df	MS		
				Number of obs	= 1841038
				F(4,1841033)	= .
Model	1.2602e+10	4	3.1506e+09	Prob > F	= 0.0000
Residual	3.2817e+10	1841033	17825.4664	R-squared	= 0.2775
				Adj R-squared	= 0.2775
Total	4.5420e+10	1841037	24670.6309	Root MSE	= 133.51

POVPIP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SCHL	12.40406	.0272896	454.53	0.000	12.35057	12.45754
WKHP	.3731615	.0056327	66.25	0.000	.3621217	.3842014
NPF	-33.68707	.0763896	-440.99	0.000	-33.83679	-33.53735
WIF	59.9064	.1368837	437.64	0.000	59.63811	60.17469
_cons	118.7567	.5560907	213.56	0.000	117.6668	119.8466

Again, each coefficient for each variable is statistically significant, as the absolute values of all the t-statistics are very large, with p-values of 0.000. The coefficient on educational attainment dropped from 15.5 in our simple regression, to 12.4 in our first multiple regression model, but this is not surprising, as we have added more variables to explain the change in income to poverty ratio. More importantly is the R-squared value went from 0.1235 in the simple regression model, to 0.2775 in this multiple regression model. We are explaining more variability in the income to poverty ratio, resulting in a better fit model. For our next model, in addition to educational attainment, we are going to include the ability to speak English, the cost of rent as a percentage of income, and health insurance coverage as independent variables. The model and regression results are below:

$$POVPIP = \beta_0 + \beta_1(SCHL) + \beta_2(ENG) + \beta_3(GRPIP) + \beta_4(HICOV) + u$$

Source	SS	df	MS		
Model	6.5797e+09	4	1.6449e+09	Number of obs =	586521
Residual	7.7080e+09	586516	13142.0726	F(4,586516) =	.
				Prob > F =	0.0000
				R-squared =	0.4605
				Adj R-squared =	0.4605
Total	1.4288e+10	586520	24360.1722	Root MSE =	114.64

POVPIP	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
SCHL	8.832909	.0406254	217.42	0.000	8.753284	8.912533
ENG	1.530057	.1617053	9.46	0.000	1.21312	1.846994
GRPIP	-3.510078	.0057289	-612.70	0.000	-3.521306	-3.498849
HICOV	-43.81732	.392335	-111.68	0.000	-44.58628	-43.04836
_cons	260.4743	.9524568	273.48	0.000	258.6075	262.3411

The coefficients are all statistically significant with p-values of 0.000. The coefficient on educational attainment is 8.83 with a very small standard error of 0.04. This coefficient is smaller than in our previous model, but the R-squared in this model is 0.4605 compared to 0.2775. This means that our income to poverty ratio increases by a slightly less amount for each increase in education, however the model is an overall better fit with the other independent variables. Also of note are the negative values on the cost of rent and health insurance coverage. We previously discussed why the cost of rent variable has a negative coefficient, and the same logic applies here. The negative coefficient on health insurance coverage is due to the manner in which the ACS codes this variable; a value of 1 is associated with having health insurance, and a value of 2 is associated with not having health insurance. Therefore, an increase from 1 to 2 in the coding of the health insurance variable will result in a decrease in the income to poverty ratio. This is logical, as people closer to poverty or in poverty are not as likely as others to be able to afford health insurance.

For our final regression model, we are going to combine the variables from the previous two models into a single model. The model and regression results are below:

$$POVPIP = \beta_0 + \beta_1(SCHL) + \beta_2(WKHP) + \beta_3(NPF) + \beta_4(WIF) + \beta_5(ENG) + \beta_6(GRPIP) + \beta_7(HICOV) + u$$

Source	SS	df	MS
Model	4.9930e+09	7	713286184
Residual	4.0940e+09	380488	10759.9563
Total	9.0870e+09	380495	23882.147

Number of obs	= 380496
F(7,380488)	=66290.81
Prob > F	= 0.0000
R-squared	= 0.5495
Adj R-squared	= 0.5495
Root MSE	= 103.73

POVPIP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SCHL	6.256694	.0455876	137.25	0.000	6.167344	6.346044
WKHP	.4269741	.0095085	44.90	0.000	.4083377	.4456106
NPF	-22.86918	.1204367	-189.89	0.000	-23.10523	-22.63313
WIF	34.92953	.2455429	142.25	0.000	34.44827	35.41079
ENG	1.228486	.1693856	7.25	0.000	.8964954	1.560477
GRPIP	-3.255922	.0074167	-439.00	0.000	-3.270458	-3.241385
HICOV	-47.14792	.4250457	-110.92	0.000	-47.98099	-46.31484
_cons	316.6653	1.137811	278.31	0.000	314.4352	318.8954

The coefficient on educational attainment is now 6.26, with a standard error of 0.046, and a t-statistic of 137.25. This means that for each unit increase in educational attainment, the income to poverty ratio increases by 6.26. Each of the other variables have coefficients that are also statistically significant, with p-values of 0.000 across the board. The R-squared for this model is 0.5495, our highest R-squared of all the models. Of course, that is expected as this model has the most independent variables, at 7 total. We can still confidently say that this model explains the most variability in the income to poverty ratio, and is the best fit, with minimal concern for multicollinearity as the sample size for this model is 380,496 individuals. Additionally, this model confirms our hypothesis that educational attainment will be positively correlated to the income to poverty ratio.

<u>Robustness Tests</u>

Now we are going to look at how the model may change if we restrict the model based on two different variables; gender and race. First, we are going to look at our best multiple regression model, restricted to only females. The model and regression results are below:

$$POVPIP = \beta_0 + \beta_1(SCHL) + \beta_2(WKHP) + \beta_3(NPF) + \beta_4(WIF) + \beta_5(ENG) + \beta_6(GRPIP) + \beta_7(HICOV) + u\,; if\ gender = female$$

Source	SS	df	MS
Model	2.6984e+09	7	385483292
Residual	2.2856e+09	209249	10922.672
Total	4.9839e+09	209256	23817.4352

Number of obs	= 209257
F(7,209249)	=35292.03
Prob > F	= 0.0000
R-squared	= 0.5414
Adj R-squared	= 0.5414
Root MSE	= 104.51

POVPIP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SCHL	6.393238	.0630571	101.39	0.000	6.269648	6.516829
WKHP	-.0282219	.0139603	-2.02	0.043	-.0555837	-.00086
NPF	-23.4191	.1669329	-140.29	0.000	-23.74629	-23.09192
WIF	42.83056	.3483023	122.97	0.000	42.1479	43.51323
ENG	2.374143	.2291805	10.36	0.000	1.924955	2.823331
GRPIP	-3.108839	.0096659	-321.63	0.000	-3.127784	-3.089894
HICOV	-47.13902	.5952712	-79.19	0.000	-48.30574	-45.9723
_cons	303.0293	1.557358	194.58	0.000	299.9769	306.0817

From these results, we calculated an F-statistic of over 30,000, meaning we can confidently say that there is a difference in the model for males and females. This is not surprising, as females still earn lower wages compared to males, often are single mothers, and can have higher health insurance premiums. Next, we will look at our multiple regression model, restricted to non-white individuals. The model and regression results are below:

$$POVPIP = \beta_0 + \beta_1(SCHL) + \beta_2(WKHP) + \beta_3(NPF) + \beta_4(WIF) + \beta_5(ENG) + \beta_6(GRPIP) + \beta_7(HICOV) + u\,; if\ race\ \neq white$$

Source	SS	df	MS
Model	1.5767e+09	7	225242135
Residual	1.3232e+09	131614	10053.9945
Total	2.8999e+09	131621	22032.5128

Number of obs	= 131622
F(7,131614)	=22403.25
Prob > F	= 0.0000
R-squared	= 0.5437
Adj R-squared	= 0.5437
Root MSE	= 100.27

POVPIP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SCHL	5.328759	.067795	78.60	0.000	5.195882	5.461636
WKHP	.3898631	.0156926	24.84	0.000	.3591059	.4206203
NPF	-20.21469	.185885	-108.75	0.000	-20.57903	-19.85036
WIF	35.16685	.3969658	88.59	0.000	34.38881	35.9449
ENG	4.288614	.2504462	17.12	0.000	3.797744	4.779484
GRPIP	-3.018298	.0114863	-262.77	0.000	-3.040811	-2.995785
HICOV	-41.04899	.6666039	-61.58	0.000	-42.35552	-39.74246
_cons	297.5994	1.764628	168.65	0.000	294.1407	301.058

With these results, we calculated an F-statistic of over 43,000, again statistically significant. We can confirm that the restricted model is different from the unrestricted model. The coefficient on educational attainment is also statistically different from the unrestricted model, showing that educational attainment's effect on the income to poverty ratio is different for whites and non-whites. These results are not surprising, as discrimination based on race is still a problem in the United States. The quality of education for many minorities is also less than that of white students, due in part to the decline of school quality in inner cities and more urban areas.

Conclusion

After working with various models, adding and subtracting different independent variables, and using different combinations of variables, our final multiple variable regression model confirms our hypothesis. Our model shows that educational attainment is positively correlated with the income to poverty ratio, with one unit increase in education resulting in the income to poverty ratio increasing by 6.26 percent. Each variable that we included in all of our models was statistically significant to the 1% level. The final model explained 54.95% of the variability of the income to poverty ratio around its mean.

We are pleased with the results of our study, as it confirmed many different widespread beliefs; including the fact that women and minorities are still discriminated against in many different areas. Perhaps most importantly, we were able to show that minorities are not getting the same amount of value from education as white individuals. This is a serious problem, and one that doesn't seem to be going away anytime soon. If education is to help reduce poverty in the United States, the quality and effectiveness of education to minorities must improve, as a large number of impoverished are minorities. This starts with improving our school systems and the quality of teachers that work in inner cities, where the concentration of low income families is the highest. If the United States can begin to improve the quality of education in inner cities, we should slowly see an increase in the effectiveness of education to increase the income to poverty ratio.

Dependent Variable Income/Poverty Ratio						
Independent Variables	Model (1)	Model (2)*	Model (3)	Model (4)	Model (5)	Model (6)*
Education	15.507***	-0.591***	12.404***	8.833***	6.257***	0.0905***
WKHP			0.373***		0.427***	0.2832***
NPF			-33.687***		-22.87***	-0.2330***
WIF			59.906***		34.93***	2.797***
ENG				1.530***	1.228***	1.376***
GRPIP				-3.510***	-3.256***	-0.2713***
HICOV				-43.817***	-47.15***	
Intercept	78.21*** (t-stat)	259.54*** (t-stat)	213.56*** (t-stat)	260.47*** (t-stat)	278.31*** (t-stat)	122.58*** (t-stat)
No. of obs.	2,356,398	297,504	1,841,038	586,521	380,496	82,945
R-square	0.1235	0.0059	0.2775	0.4605	0.5495	0.1356

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